

# Quantifying Errors Associated with Satellite-Derived Data Sets

A feeble attempt to initiate a discussion with NASA Science Teams

Peter Cornillon

University of Rhode Island

New Orleans  
Earth Science Data System Working Groups'  
joint meeting

20 October 2009

## 1 The Poll

## 2 Spatial Fidelity

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- 17 August Product Quality Metrics Telecon I suggested

- Including the quality of spatial information as a fundamental data set metric
- Gathering information from NASA Science teams about their plans/approaches to quality metrics
  - Rama asked if I would coordinate this.
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- Reflectivity data set

- Merging 10 to 11 satellites
- 31 years

- Measuring reflectivity back to space.

- No ground-based data for validation.

- Two approaches to validation and error estimates.

- Compare ground irradiance estimated from reflected energy reaching space with ground-based irradiance measurements.
- Consider the precision of the data rather than their accuracy.
  - Based on initial laboratory calibration of the satellite instrument
  - From the reflectivity measurements in flight
  - Methods of combining satellite data

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Fidelity

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- With regard to the telecon, Lucien suggested
  - We identify a minimum list of criteria for data quality on which we all agree.
    - If too long of a list, people will not provide the metrics
- Focus on one example first and then see how it can be generalized.
- Values without error bars are almost meaningless.
  - It is doubtful that a product without error bars can be classified as "high quality"
- Error bars in atmospheric composition tend to come as:
  - Precisions on individual profiles
  - Accuracy estimates based on error characterization studies

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# Input from Bob Evans

- UMiami focus is on the quality of global satellite-derived SST fields

- Although SST is the most completely sampled parameter of the Earth system, there are regions that are undersampled

- Poleward of 60°
- Upwelling zones (thinking IR here)
- Areas with confounding atmospheric situations - dust, aerosols

- UMiami uses two approaches to estimate SST uncertainty

- Uncertainty Hypercube

- Uncertainty determined by partitioning each 1° up into 8 environmental spaces
- 1000 samples

- - Latitude band

- - Longitude band

- - Depth range

- - Bathymetry comparison SST anomaly

- - Bathymetry satellite SST anomaly

- - Duration

- The uncertainty hypercube allows for a statistical analysis of SST quality across numerous conditions

- It is used as a visual overview of uncertainty in comparison with the best of any one field

- It is also used as a tool to compare the quality of the various satellite SST products

- Below

- Compare satellite SST fields

- In this case, the best available measurement provided the highest standard of accuracy

- The discrepancy between the quality of the satellite SST measurements is more apparent in the form of the distribution of uncertainty measures

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- Uncertainty hypercube for monitoring data from a 10° x 10° grid cell

- Oceanographic

- Atmospheric

- Instrumental

- Radiometric

- Statistical satellite SST errors

- Oceanographic

- Oceanographic hypercube: differences from oceanographic parameters (e.g. salinity, density, etc.)

- Atmospheric

- Atmospheric hypercube: differences from atmospheric parameters (e.g. wind, humidity, etc.)

- Instrumental

- Compare satellite SST fields

- Use the same hypercube for monitoring data from a 10° x 10° grid cell

- Use Oceanographic hypercube for differences from oceanographic parameters (e.g. salinity, density, etc.)

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● Uncertainty hypercube for each parameter, each time step, each spatial region

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## ● UMiami uses two approaches to estimate SST uncertainty

### ● Uncertainty Hypercube

● Hypercube is a tool used for quantifying uncertainty in a multidimensional space

● Example: SST

● SST is a function of

● Time

● Space

● Wavelength

● Sensor

● Platform

● Data processing

● Data quality

● Data coverage

● Data resolution

### ● Compare satellite SST fields

● UMiami has one hypercube for each satellite SST product (e.g. AVHRR, SeaWiFS, etc.)

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How much uncertainty is associated with a given SST value? How much is associated with a given location?

How much is associated with a given time?

How much is associated with a given sensor?

How much is associated with a given algorithm?

How much is associated with a given model?

How much is associated with a given data source?

How much is associated with a given data type?

How much is associated with a given data format?

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How much is associated with a given data content?

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How much is associated with a given data environment?

How much is associated with a given data system?

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  - Uncertainty Hypercube
    - Uncertainty determined by partitioning match-up into a 7 dimensional space
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      - Brightness temperature difference
      - Retrieved satellite SST quality level
      - Day/night.
    - The uncertainty hypercube allows for a statistical estimate of SST under similar observing conditions.
    - It is not a direct measure of uncertainty associated with the SST of a given pixel.
    - As the analysis includes more parameters, the number of in situ obs becomes limiting.
  - Compare satellite SST fields
    - No one field or in situ measurement provides an absolute standard of reference
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- NASA has formed an SST Science Teaming
- A pre-SSTST workshop was held in Rhode Island in November 2009
  - Workshop objective was to characterize the SST error budget
  - An SST error budget white paper was produced following the workshop:  
[http://www.ssterrorbudget.org/ISSTST/White\\_Paper.html](http://www.ssterrorbudget.org/ISSTST/White_Paper.html)

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CDR	Ohring et al., 2005				0.1	0.04°K/decade
CDR	<a href="#">Appendix II</a>					0.05°K/decade
NWP	Eyre et al., 2009	5	3		0.3	
Global Operations	NPOESS IORD-II	0.25	3	0.1	0.1	0.05°K
Coastal/Lake Operations	NPOESS IORD-II	0.1	6	0.1	0.1	
Fronts	<a href="#">Appendix II</a>	0.1	0.25	0.1	1	0.1°K
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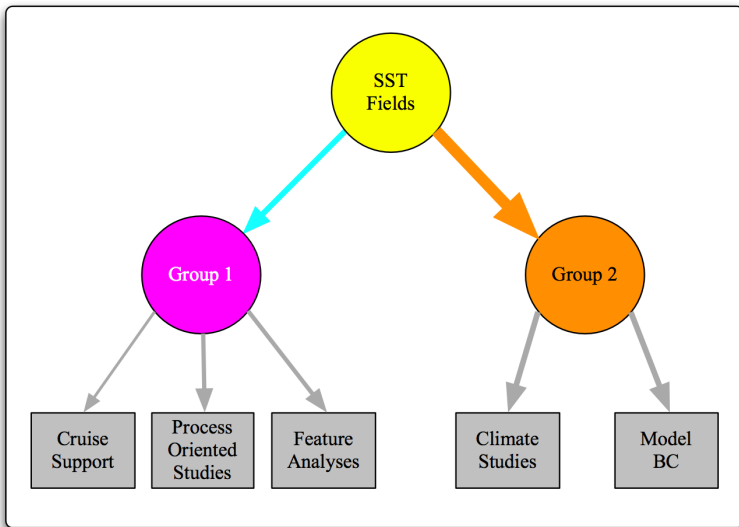
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# Feature versus Climate Studies

Peter  
Cornillon

The Poll

Spatial  
Fidelity



- Satellite-derived Earth science data sets are rich both

- Temporally, and
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- However, we rarely evaluate the quality of spatial information in our data products.

Although the previous and following comments may apply to other Earth science disciplines  
Those presented here are based on observations associated with ocean products.

- Primary focus of the quality of most satellite-derived products is on 'point' accuracy.

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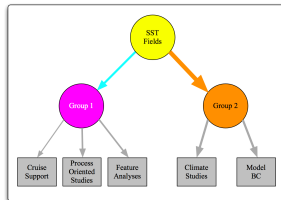
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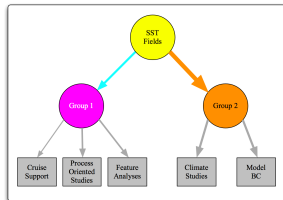


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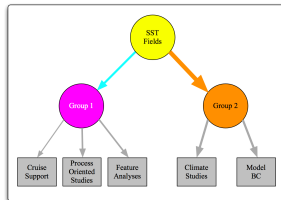


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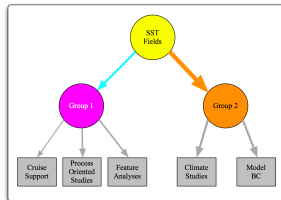


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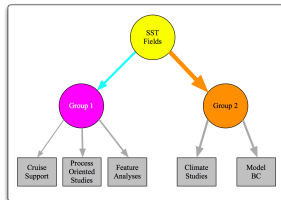


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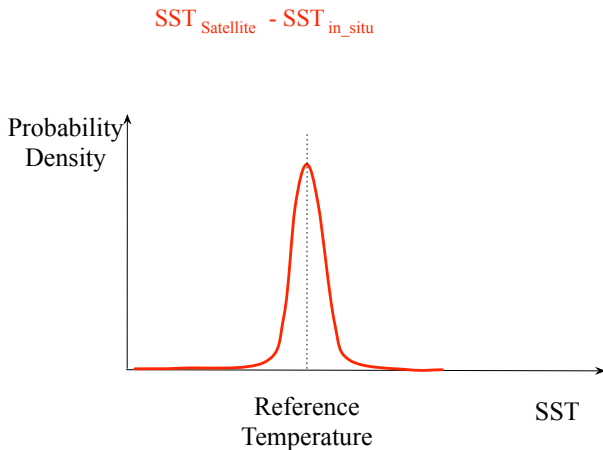
New requirements point to the need for a measure of the spatial fidelity of SST products.

# Accurate and Precise

Peter  
Cornillon

The Poll

Spatial  
Fidelity



Small scatter, no bias

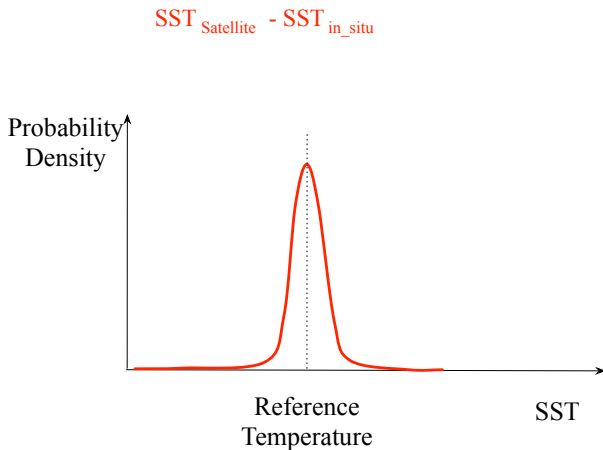


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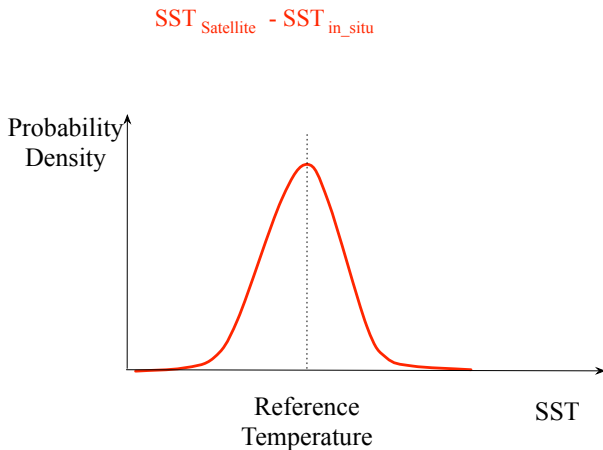
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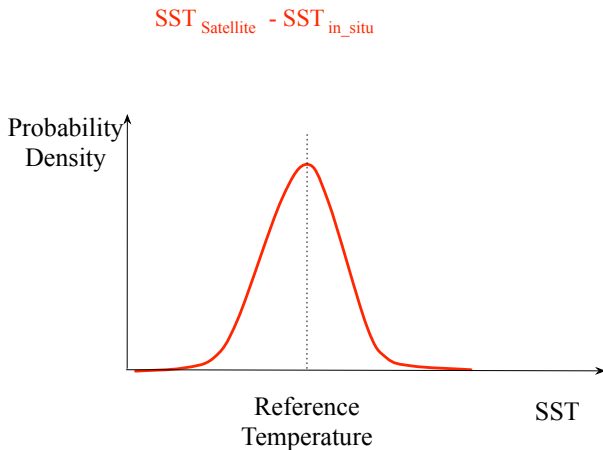
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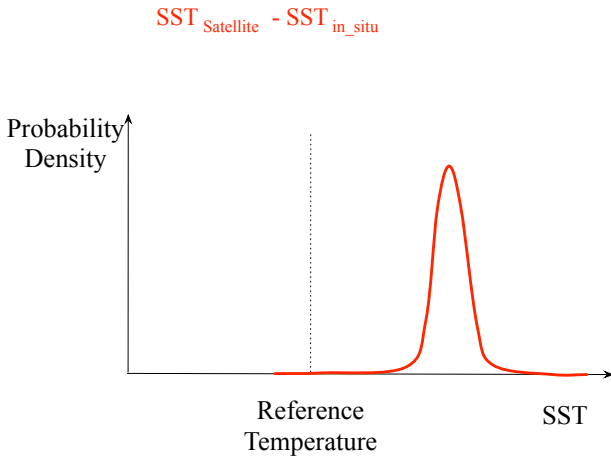
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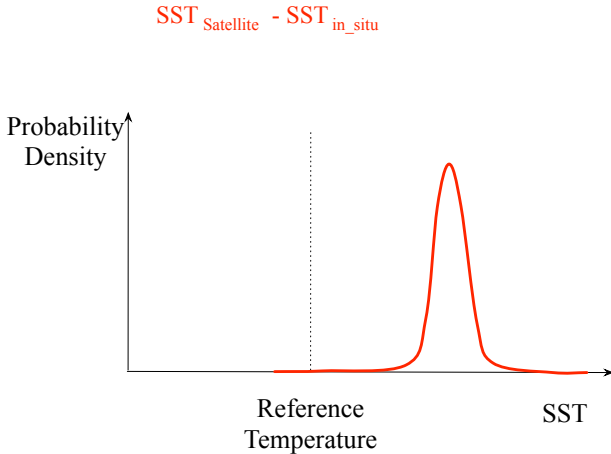
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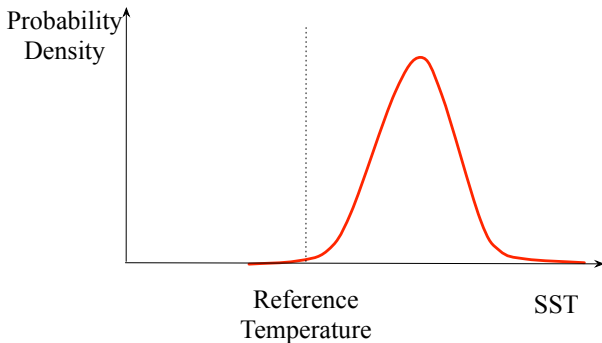
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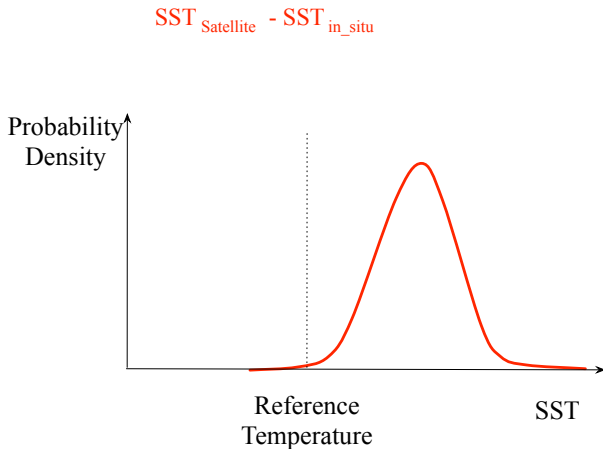
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Now let's look at these distributions in the context of the point-to-point (spatial) difference in an SST field.



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# Accurate and Precise; Small Point-to-Point

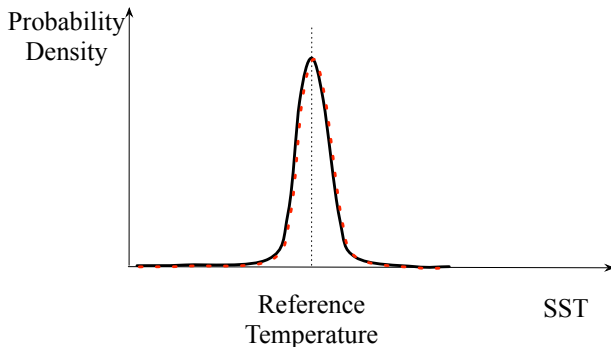
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Small scatter, no bias when compared with in situ observations  
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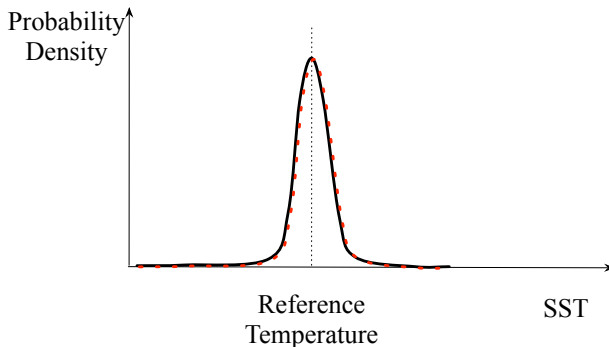
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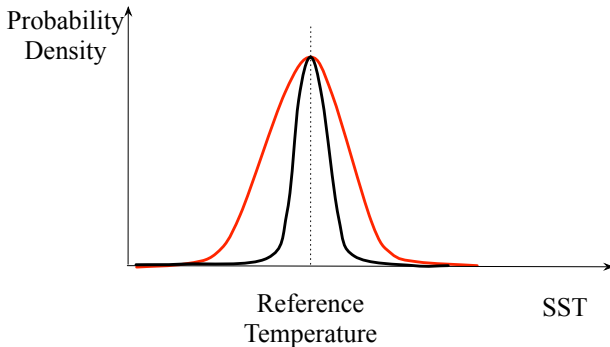
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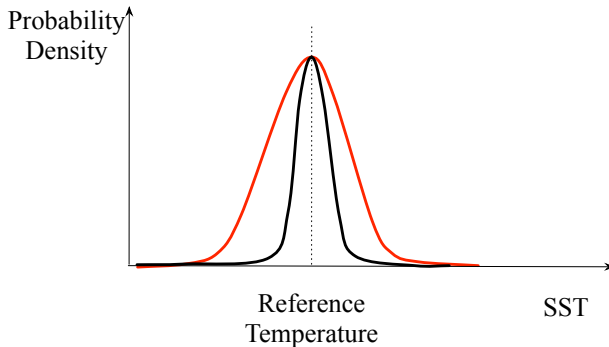
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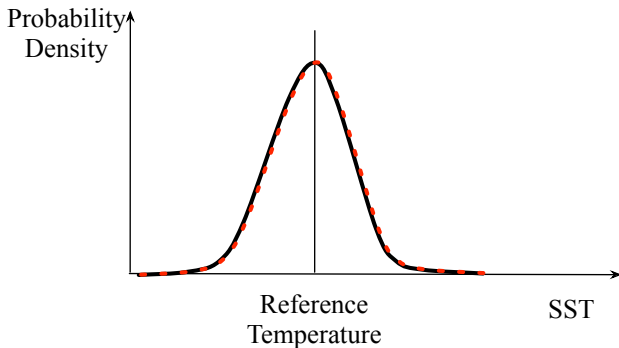
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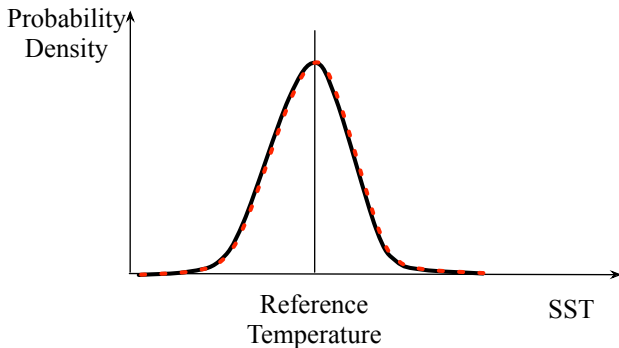
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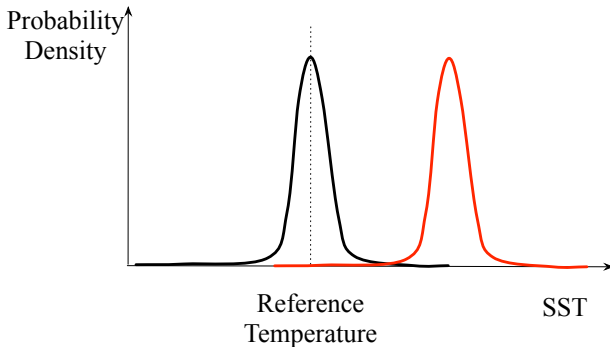
Peter  
Cornillon

The Poll

Spatial  
Fidelity

$$SST_{\text{Satellite}} - SST_{\text{in_situ}}$$

$$SST(i, j)_{\text{Satellite}} - SST(i+1, j)_{\text{Satellite}}$$



Small scatter, large bias when compared with in situ observations  
and small point-to-point variability

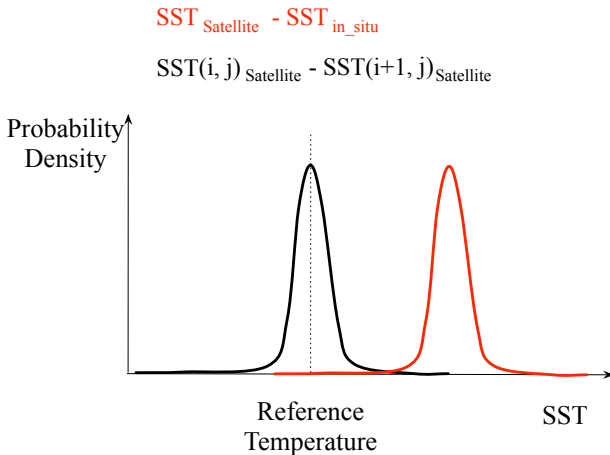


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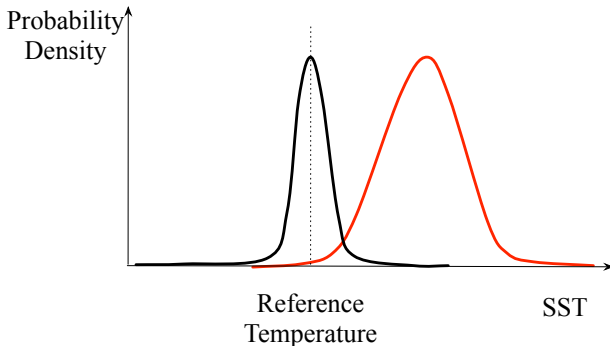
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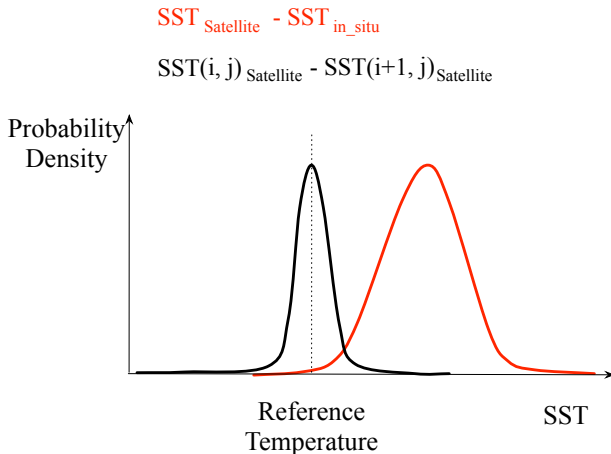
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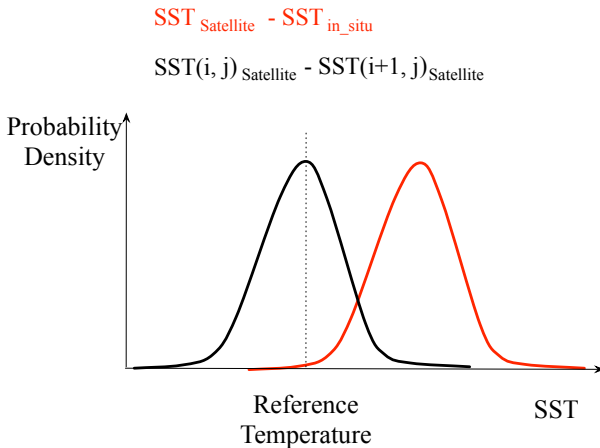
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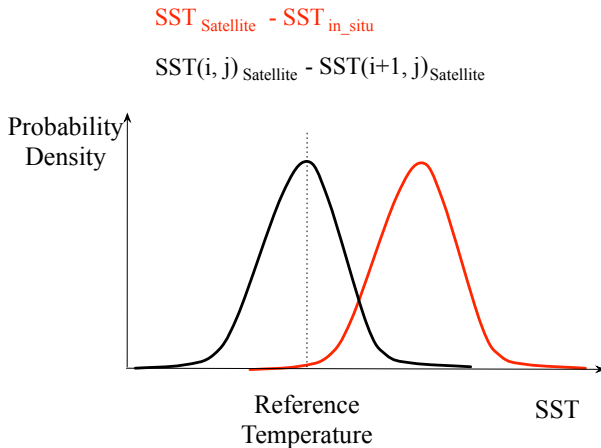
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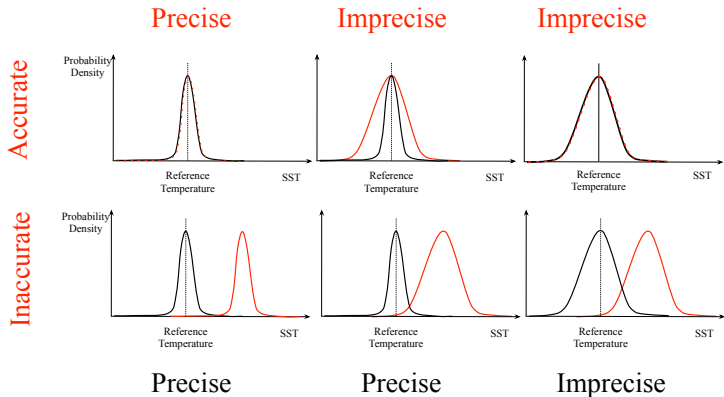
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# All Together Now

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Cornillon

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Spatial  
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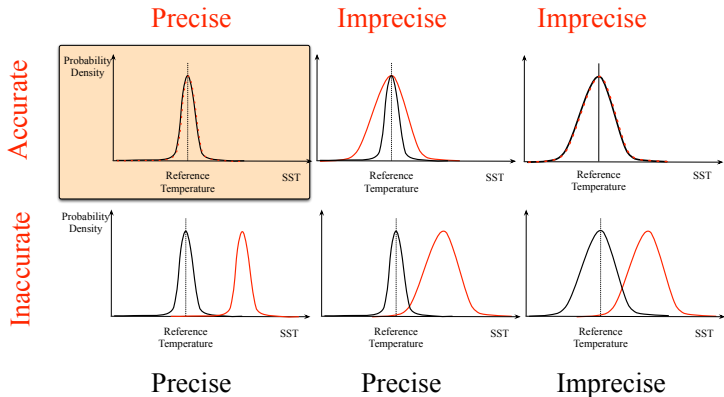


# All Together - Climate Studies

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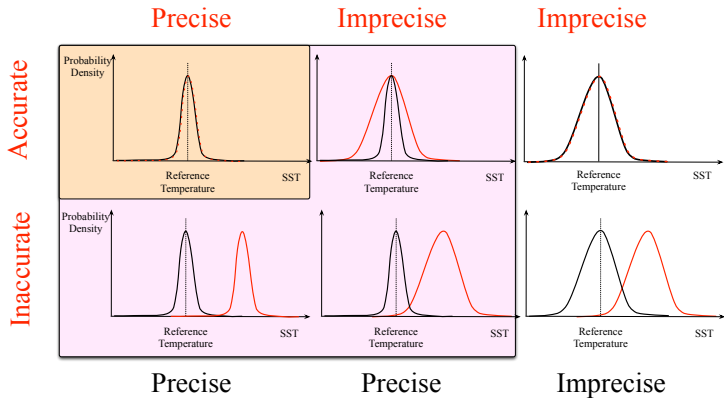


# All Together - Feature Studies

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Cornillon

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# Examples: Case 1

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Let's look at a couple of simple statistics for two different cases.

- **Comparison 1: For the western North Atlantic**
  - The data sets
    - MODIS - 4km global for 2008
    - AVHRR Pathfinder v5 - 4km global for 2008
  - The statistic
    - The standard deviation for each 3x3 pixel tile in each image.

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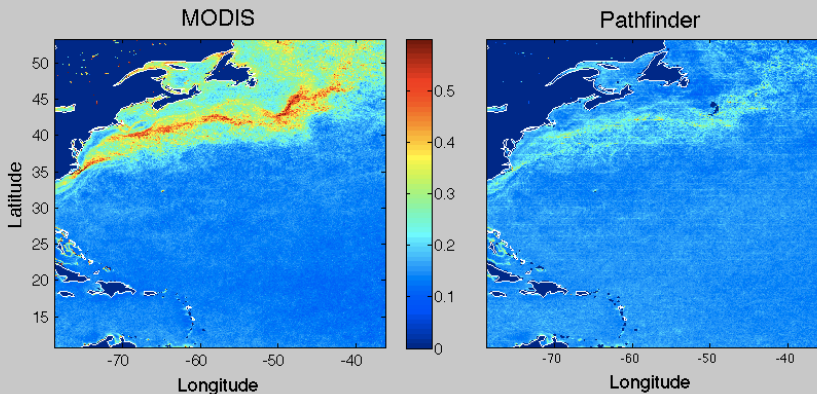
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# Standard Deviation on 3x3 Tiles

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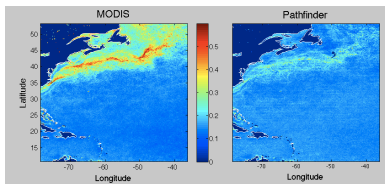
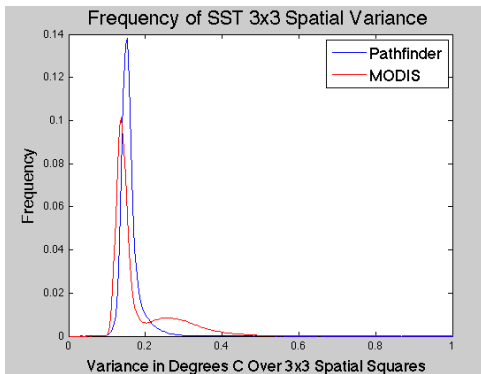


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And

- Comparison 2: For the world ocean
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    - Level 3 AMSR-E from RSS obtained from L2 and reprojected to a 25km resolution map.
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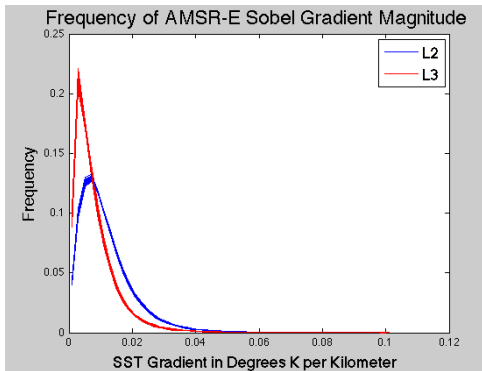
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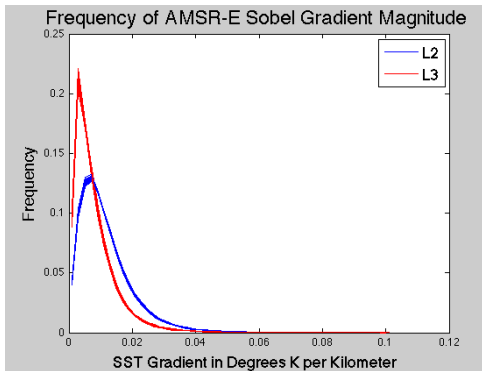
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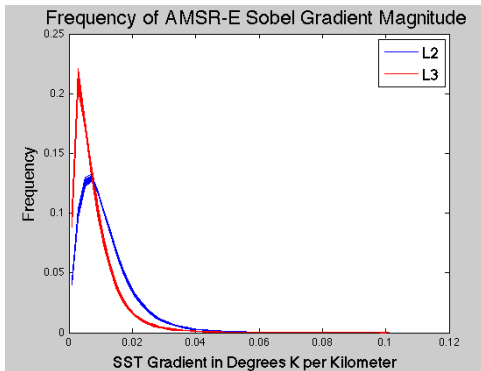


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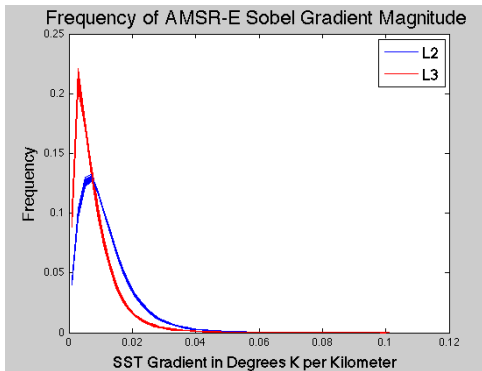
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- Two similar sensors with similar processing (MODIS/AVHRR)
- Yield quite different results for a statistic related to the spatial variability of the fields.
- Two data sets from the same sensor but in different projections (L2/L3)
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It seems a shame to spend BILLIONS of \$s on collecting data and then to ignore some of their richness.

# The End